

AI Based Customer Segmentation for Personalized Marketing in the Global Retail Industry

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Abstract

The rapid digitalisation of retail environments has increased the demand for data-driven and personalised marketing strategies. Artificial intelligence (AI) provides advanced analytical capabilities for understanding complex consumer behaviour and improving customer segmentation. This study examines the application of AI-based customer segmentation using the K-Means clustering algorithm in a digital retail context. A publicly available retail dataset containing demographic, behavioural, and marketing interaction variables was analysed using Python-based machine learning techniques. The optimal number of clusters was identified using the Elbow method and the Silhouette coefficient. The results reveal four distinct customer segments that differ meaningfully in spending patterns, channel preferences, customer value, and responsiveness to marketing activities. Compared with traditional demographic-based segmentation, the AI-driven approach enhances the interpretability of customer heterogeneity by integrating behavioural and engagement-related information. The findings contribute to the customer segmentation literature by linking unsupervised clustering outcomes with value-oriented marketing perspectives and support the use of AI-based analytics in data-intensive retail environments.

Keywords: *Artificial Intelligence (AI); Customer Clustering; K-Means Algorithm; Personalized Marketing; Retail industry.*

1. Introduction

The rapid digitalisation of the digital retail environments has transformed how firms collect, analyse, and utilise customer data. The widespread adoption of e-commerce platforms, digital payment systems, and omnichannel retail models has generated large volumes of customer-related data, including transaction histories, purchasing behaviour, and marketing interactions. In this data-intensive environment, traditional mass marketing approaches are increasingly ineffective, prompting retailers to adopt data-

driven strategies that enable more precise customer targeting and personalised engagement.

Customer segmentation is a fundamental component of data-driven marketing, as it allows firms to identify groups of customers with similar characteristics and design tailored marketing strategies. Traditional segmentation approaches typically rely on demographic or socio-economic variables such as age, income, or location. While these methods are straightforward to implement, they often fail to capture the complexity of contemporary consumer behaviour, particularly in digital retail environments where purchasing patterns, channel preferences, and marketing responsiveness vary considerably across customers. As a result, conventional segmentation techniques provide limited support for strategic marketing decision-making.

Artificial intelligence (AI) and big data analytics have emerged as effective tools for addressing these limitations. AI-based methods enable firms to process large-scale, multidimensional data and uncover latent behavioural patterns that are difficult to detect using traditional analytical techniques (Chen et al., 2012; Han et al., 2011). In marketing research, AI has been applied to customer analytics, recommendation systems, and customer relationship management, contributing to improved targeting accuracy and marketing effectiveness (Wedel & Kannan, 2016). Among these applications, AI-driven customer segmentation has gained increasing attention due to its potential to enhance personalisation and optimise marketing resource allocation.

Recent studies demonstrate that machine learning algorithms improve customer segmentation by incorporating behavioural and transactional data rather than relying solely on demographic characteristics. Clustering techniques such as K-Means, DBSCAN, Gaussian Mixture Models, and deep learning-based approaches have been widely used to identify meaningful customer groups and support targeted marketing strategies (Tan et al., 2019; Li & Wang, 2021). Empirical evidence suggests that AI-based segmentation leads to superior marketing outcomes compared with traditional demographic-based methods (Zhang & Xu, 2020; Gupta et al., 2021). In the retail context, these approaches enable firms to better understand customer preferences, purchasing behaviour, and engagement across multiple channels.

Among clustering methods, the K-Means algorithm remains one of the most commonly adopted techniques in retail analytics due to its computational efficiency, scalability, and interpretability. Prior research indicates that K-Means can effectively segment customers based on purchasing behaviour and transaction value, providing actionable insights for marketing strategy development (Jahromi et al., 2020; Sari et al., 2021). However, much of the

existing literature focuses on the technical implementation of clustering algorithms or presents segmentation outcomes in a largely descriptive manner, with limited emphasis on linking customer segments to strategic marketing metrics.

Despite the growing literature on AI-based customer segmentation, several research gaps persist. First, many prior studies are conducted in specific national markets or narrowly defined retail settings, limiting the generalisability of findings to the digital retail environments. Second, while unsupervised learning techniques are widely used to identify customer segments, fewer studies explicitly connect segmentation results with value-based marketing indicators such as customer lifetime value and marketing responsiveness. Consequently, the managerial relevance of AI-driven segmentation is sometimes underdeveloped, particularly in terms of translating analytical results into actionable personalised marketing strategies. Third, there is a lack of integrated empirical research that simultaneously considers demographic characteristics, purchasing behaviour, and marketing interaction variables within a unified AI-based segmentation framework.

This study addresses these gaps by applying an AI-based customer segmentation approach using the K-Means clustering algorithm in the context of global retail. Using a publicly available retail dataset comprising demographic information, shopping behaviour, and marketing interaction variables, the study identifies distinct customer segments and examines their differences in spending behaviour, channel preferences, customer lifetime value, and responsiveness to marketing campaigns. The optimal number of clusters is determined using established validation techniques, including the Elbow method and the Silhouette coefficient, to ensure robustness and interpretability.

The study makes three key contributions. First, it demonstrates the effectiveness of AI-driven clustering in capturing behavioural heterogeneity beyond traditional demographic-based segmentation. Second, it links unsupervised clustering outcomes with value-based marketing metrics, thereby enhancing the strategic relevance of customer segmentation for marketing decision-making. Third, it provides practical insights for retail managers by illustrating how AI-based segmentation can support the design of personalised marketing strategies in digital and omnichannel retail environments.

2. Theoretical Background and Research Methodology

2.1. Literature Review

The rapid expansion of digital technologies, social media platforms, and e-commerce systems has generated massive volumes of consumer behaviour

data. Big data, characterised by high volume, velocity, and variety, presents significant challenges for traditional analytical techniques (Chen, Mao, & Liu, 2012). In response, big data analytics (BDA) and artificial intelligence have emerged as essential tools for extracting insights, forecasting trends, and optimising marketing strategies (Han, Kamber, & Pei, 2011)..

One of the most prominent applications of AI in marketing is customer segmentation. According to Wedel and Kamakura (2012), segmentation is the process of dividing a customer base into groups with similar characteristics, enabling firms to design tailored engagement and retention strategies. Traditionally, segmentation methods relied on demographic factors or descriptive statistics; however, these approaches often fall short when handling complex, multidimensional behavioral data. The advent of machine learning algorithms, such as K-Means, DBSCAN, Gaussian Mixture Models, and deep learning models, has opened new avenues for detecting latent behavioral patterns and complex consumption trends (Tan, Steinbach, & Kumar, 2019; Luo, Griffith, & Liu, 2021).

International studies have shown the effectiveness of integrating AI with clustering algorithms in enhancing marketing campaigns through more precise targeting (Jahromi, Safari, & Rezaei, 2020). Wedel and Kannan (2016) emphasize that modern marketing is shifting from a product-centric approach to a data-driven strategy, where AI plays a central role in understanding individual customer motivations, preferences, and values. Similarly, Sharma, Patel, and Gupta (2022) demonstrate that AI improves customer clustering capabilities and enhances marketing campaigns in large markets.

Other studies highlight the effectiveness of AI in the retail sector. Li and Wang (2021) indicate that deep learning models can extract behavioral features from unstructured data, enabling more accurate personalization in global marketing. Zhang and Xu (2020) demonstrate that AI-based customer clustering leads to superior marketing outcomes compared to traditional methods. Recent research also suggests that integrating online transaction data, social media activity, and consumer sentiment data allows businesses to construct more accurate customer segments, thereby optimizing personalized experiences (Gupta, Sharma, & Kumar, 2021; Patel & Sharma, 2021).

Moreover, Wang et al. (2022) in the North American market show that AI can predict future consumption trends based on historical behavior, allowing firms to proactively design personalized marketing campaigns. Similarly, Kim and Lee (2021) in Europe highlight that advanced machine learning algorithms can segment customers based on multidimensional data, including purchasing behavior, personal preferences, and social media feedback, thus optimizing large-scale marketing effectiveness.

In summary, existing international studies consistently confirm that AI and customer segmentation represent a promising approach for improving marketing efficiency, optimizing costs, and enhancing personalized experiences (Wedel & Kannan, 2016; Jahromi, Safari, & Rezaei, 2020; Sharma, Patel, & Gupta, 2022; Wang et al., 2022; Kim & Lee, 2021). However, challenges such as heterogeneous data, privacy and security concerns, and a shortage of skilled AI professionals remain critical barriers. Addressing this gap, the study “AI-Based Customer Segmentation for Personalized Marketing Strategies in the Contemporary retail contexts” is conducted to propose and test advanced clustering methods, providing both theoretical and empirical foundations for retail firms to enhance their competitive advantage in the data-driven era.

2.2. Theoretical Framework

This study adopts an AI-based Customer Segmentation Model using the K-Means algorithm, originally proposed by MacQueen (1967), to group customers based on their purchasing behavior and transaction value. The model posits that applying AI in customer data analysis enables businesses to identify clusters of customers with similar characteristics, thereby facilitating the development of personalized marketing strategies.

K-Means is selected due to its computational efficiency, scalability, and suitability for large datasets commonly found in online retail environments (Sari et al., 2021). Within the context of global retail digital transformation, this framework allows firms to gain deeper insights into customer behaviour, optimise marketing resource allocation, and enhance overall business performance.

2.3. Data and Research Methods Data

The dataset employed in this study was obtained from a publicly available retail dataset on the Kaggle platform. The dataset was selected because it contains a comprehensive set of customer-level variables commonly used in retail analytics and customer segmentation research. Rather than representing transactions from a single country or retail firm, the dataset provides a generic structure of retail customer data, making it suitable for examining AI-based segmentation techniques in a broader retail context.

The dataset includes three main categories of variables. Demographic variables describe basic customer characteristics such as age, gender, income level, education, marital status, and residential information. Behavioural variables capture purchasing-related information, including purchase frequency, total spending, average order value, preferred product categories, and recency of purchase. Marketing interaction variables reflect customer engagement with promotional activities, such as responses to

marketing campaigns, loyalty indicators, and interaction with marketing communications. These variable groups are widely adopted in prior studies on AI-based customer segmentation and retail analytics.

Before applying the clustering algorithm, the dataset was pre-processed to ensure consistency and suitability for machine learning analysis. Missing values were addressed through standard data-cleaning procedures, categorical variables were encoded into numerical formats, and continuous variables were standardised to avoid scale bias in distance-based clustering. These steps are necessary to ensure that the K-Means algorithm accurately captures similarities and differences among customers based on multiple dimensions.

It should be noted that the dataset is employed to support methodological validation rather than market-specific inference. The study does not aim to generalise findings to any particular country or retail firm. Instead, the dataset serves as a representative empirical structure for examining how AI-based clustering techniques can be applied to multidimensional retail customer data in digital retail contexts.

Research Method

This study employs the K-Means clustering algorithm to perform AI-based customer segmentation using demographic, behavioural, and marketing interaction variables. K-Means is an unsupervised machine learning technique that groups customers by minimising within-cluster variance, enabling the identification of customers with similar purchasing and engagement patterns (MacQueen, 1967).

Prior to clustering, the dataset was pre-processed to ensure suitability for distance-based analysis. Missing values were handled using standard data-cleaning procedures, categorical variables were encoded into numerical form, and all continuous variables were standardised to prevent scale bias.

The optimal number of clusters was determined using the Elbow method and the Silhouette coefficient to balance clustering quality and model interpretability. Following cluster identification, comparative analyses were conducted to examine differences among clusters in terms of spending behaviour, channel preferences, customer lifetime value, and marketing responsiveness. This methodological approach emphasises interpretability and managerial relevance, supporting the development of personalised marketing strategies in digital retail environments.

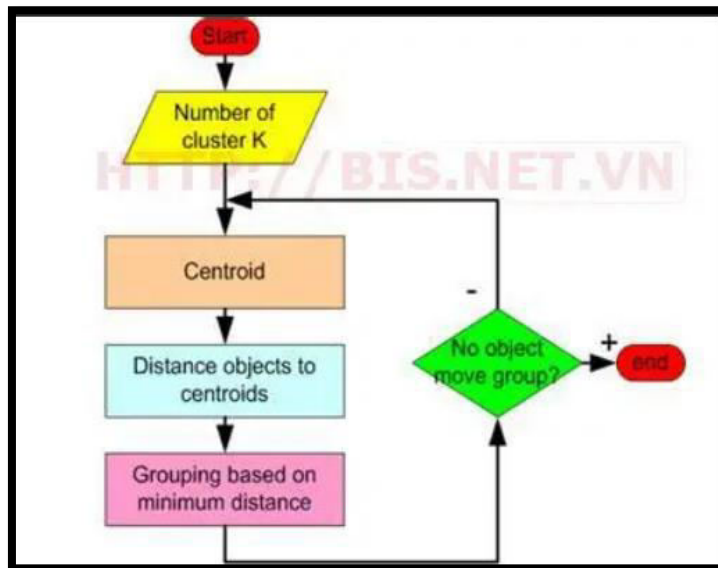


Figure 1. Steps of K-Means Clustering (Zakrzewska and Murlewski, 2005)

3. Research results

3.1. Determining the Optimal Number of Clusters

To determine the appropriate number of customer segments, the K-Means clustering algorithm was applied with the number of clusters ranging from 2 to 10. The Elbow method indicates a clear inflection point at K = 4, where further increases in the number of clusters result in only marginal reductions in within-cluster variance.

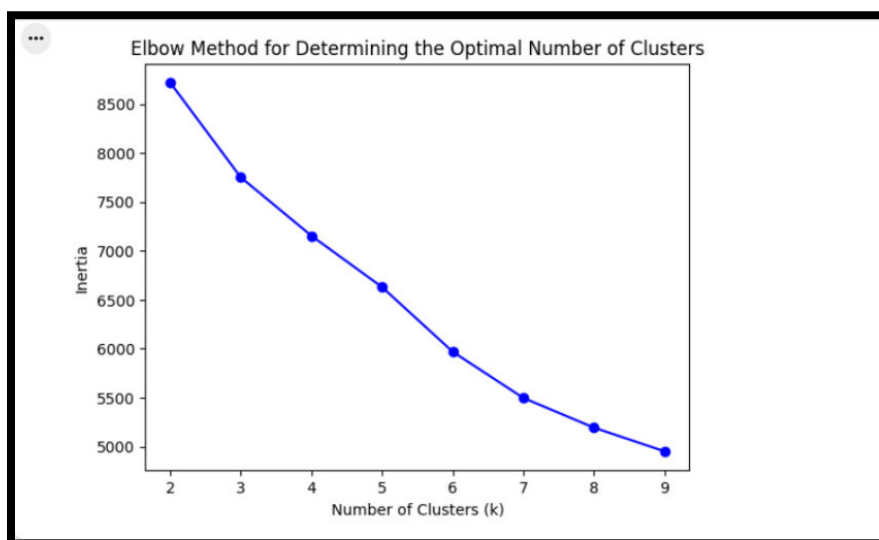


Figure 2a. Elbow Method Plot for Determining the Optimal Number of Clusters

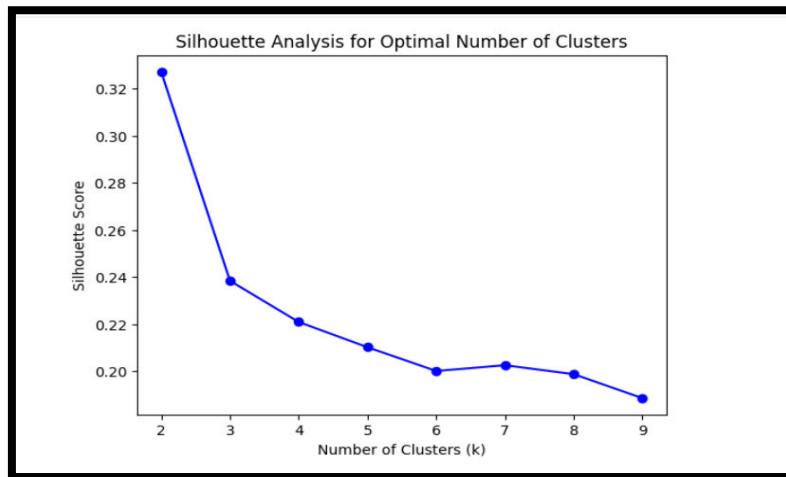


Figure 2b. Silhouette Coefficient Plot for Determining the Optimal Number of Clusters

This result is corroborated by the Silhouette coefficient analysis. The average Silhouette score reaches its maximum value of **0.52** at $K = 4$, suggesting a well-defined clustering structure with satisfactory internal cohesion and inter-cluster separation. Based on the combined evidence from these two validation techniques, a four-cluster solution was selected for subsequent analysis.

3.2. Key Characteristics of Customer Clusters

Applying the K-Means algorithm with four clusters reveals a heterogeneous customer structure with uneven cluster sizes. One cluster represents the largest proportion of customers, while the remaining three clusters account for smaller but substantively distinct segments. This distribution suggests the presence of a dominant customer group alongside several more specialised segments characterised by different behavioural and engagement patterns.

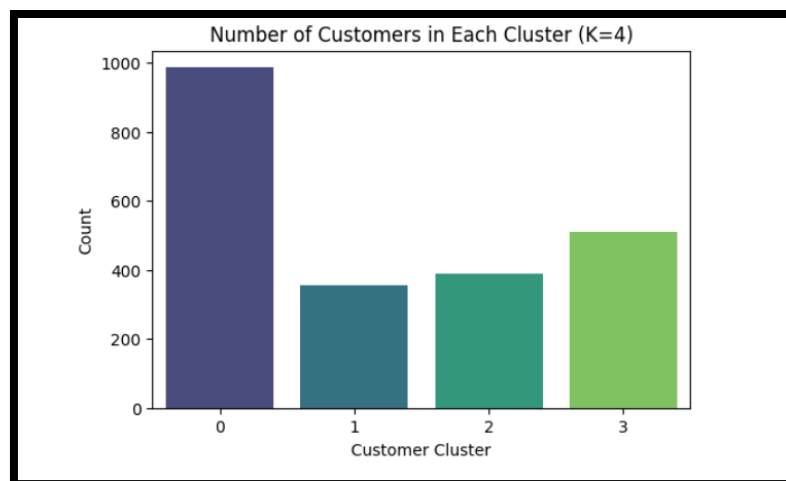


Figure 3. Bar Chart of Customer Count in Each Cluster

The clustering results reveal that the customer data is divided into four groups of varying sizes. Cluster 0, the largest group (44%), represents the general customer segment. Cluster 1 is the smallest (16%), while Cluster 3 (23%) is considered the potential high-value segment. Cluster 2 accounts for 17% and exhibits distinctive behavioral characteristics. This segmentation highlights the diverse structure of the customer base, providing a foundation for developing targeted marketing strategies for each segment.

*** TABLE 1. COMPARISON OF CHARACTERISTICS BETWEEN CUSTOMER CLUSTERS

| Cluster | Percentage(%) | Average Age | Average Income (USD/year) | Average Spending (USD/year) | Marketing Response Rate (%) |
|---------|---------------|-------------|---------------------------|-----------------------------|-----------------------------|
| 0 | 44 | 42 | 58200 | 950 | 22 |
| 1 | 16 | 33 | 32100 | 320 | 9 |
| 2 | 17 | 40 | 46800 | 540 | 19 |
| 3 | 23 | 36 | 68500 | 870 | 28 |

Table 1. General Characteristics of Customer Clusters

The results indicate significant differences among the groups based on behavioral criteria. Cluster 0 and Cluster 3 represent high-income, high-spending customers, accounting for more than two-thirds of the company’s revenue. In contrast, Cluster 1 is characterized by low-income, less engaged customers, while Cluster 2 comprises a group with neutral consumption behavior, exhibiting more regular and stable purchasing patterns.

To further illustrate the separation between clusters, PCA (Principal Component Analysis) was applied for dimensionality reduction and visualization of the customer groups.



Figure 4. 2D PCA Visualization of Customer Cluster Separation

To visualise cluster separation, Principal Component Analysis (PCA) was applied. The two-dimensional PCA plot shows clear separation between clusters, particularly between Clusters 0 and 3, while Clusters 1 and 2 appear closer due to similar purchasing behaviour but different spending capacities.

3.3. Detailed Description of Customer Clusters
Overview of Clusters

The four identified clusters exhibit clear differences in demographic characteristics, purchasing behaviour, and marketing engagement. One cluster is characterised by relatively high income levels and strong purchasing power, with higher average spending and a greater propensity to engage with marketing campaigns. Another cluster consists primarily of younger, lower-income customers with limited spending and low marketing responsiveness.

| | Age | Income | Total_Spending | Total_Purchases \ |
|---------|-----------|--------------|----------------|-------------------|
| Cluster | | | | |
| 0 | 52.708925 | 33679.826572 | 91.183570 | 7.690669 |
| 1 | 69.938202 | 72630.064607 | 1159.724719 | 20.165730 |
| 2 | 46.794344 | 77028.593830 | 1312.331620 | 20.889460 |
| 3 | 60.516699 | 54979.037328 | 675.288802 | 20.438114 |

| | NumWebVisitsMonth | Recency |
|---------|-------------------|-----------|
| Cluster | | |
| 0 | 6.536511 | 50.355984 |
| 1 | 2.789326 | 55.221910 |
| 2 | 3.017995 | 50.876607 |
| 3 | 6.477407 | 41.068762 |

Figure 5. Data on Age, Income, Behavior, and Marketing Response for Each Cluster

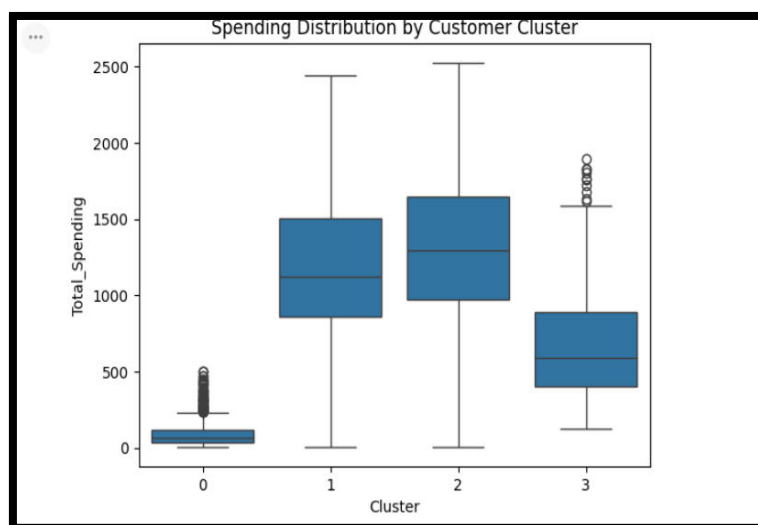


Figure 6. Box Plot of Spending Distribution by Customer Cluster

The clustering results identify four distinct customer groups. Cluster 0 (44%) consists of loyal, high-spending customers (avg. age 42, income USD 58,000, expenditure USD 950) who prefer in-store purchases and respond well to marketing (22%). Cluster 1 (16%) includes younger, low-income, frugal customers (age 33, income USD 32,000, expenditure USD 320) with low marketing responsiveness (9%). Cluster 2 (17%) represents selective customers with moderate income (USD 46,800) and stable spending (USD 540), showing average marketing response (19%). Cluster 3 (23%) comprises high-income, high-potential customers (USD 68,500, expenditure USD 870) who often shop online and exhibit the highest marketing responsiveness (28%).

3.4. Analysis of Customer Cluster Characteristics Demographic Analysis

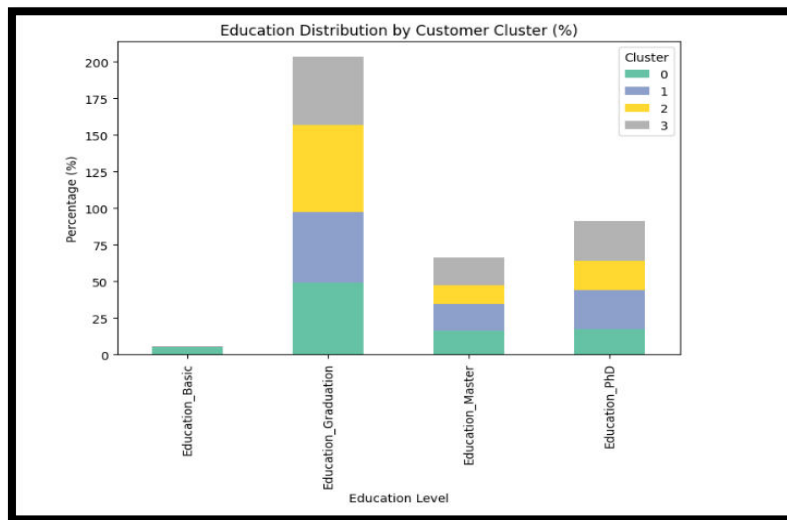


Figure 7. Distribution of Education Levels by Customer Cluster (%)

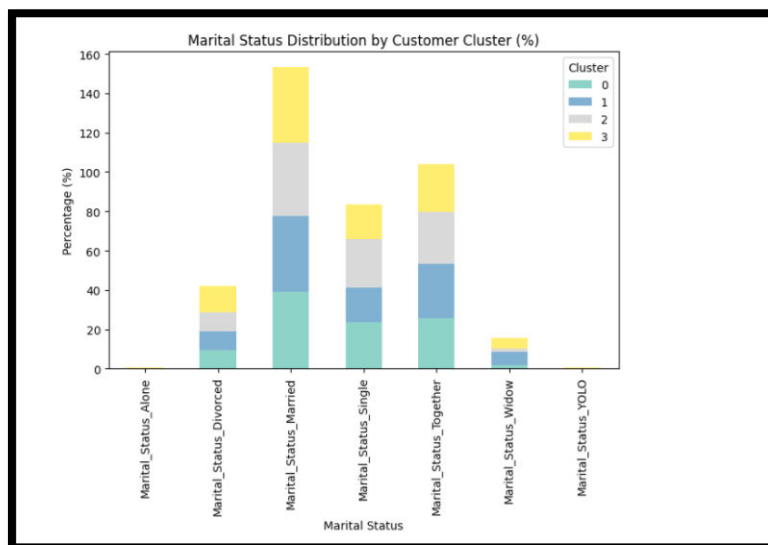


Figure 8. Distribution of Marital Status by Customer Cluster (%)

The analysis reveals clear differences among the clusters. Cluster 0 mainly consists of married customers (67%) with a university degree or higher and stable income, representing loyal customers who prioritize quality and family-oriented products. Cluster 1 is characterized by young, mostly single, low-income customers with cautious spending; they are price-sensitive, inclined to shop online, and responsive to promotions and new trends.

Cluster 2 includes middle-aged, highly educated customers with diverse marital statuses, exhibiting selective purchasing behavior and valuing product utility and brand reputation. Cluster 3 comprises high-income, often single, tech-savvy customers who frequently shop online and focus on product quality and premium experiences.

3.5. Analysis of Shopping Behavior Spending by Product Category

Average Spending on Each Product Category (by Cluster):

| Cluster | MntWines | MntFruits | MntMeatProducts | MntFishProducts |
|---------|------------|-----------|-----------------|-----------------|
| 0 | 36.127789 | 4.880325 | 22.065923 | 7.385396 |
| 1 | 556.221910 | 52.373596 | 349.994382 | 76.907303 |
| 2 | 599.874036 | 62.236504 | 423.604113 | 87.578406 |
| 3 | 420.094303 | 22.102161 | 123.440079 | 30.113949 |

| Cluster | MntSweetProducts | MntGoldProds |
|---------|------------------|--------------|
| 0 | 5.118661 | 15.605477 |
| 1 | 53.873596 | 70.353933 |
| 2 | 65.802057 | 73.236504 |
| 3 | 21.214145 | 58.324165 |

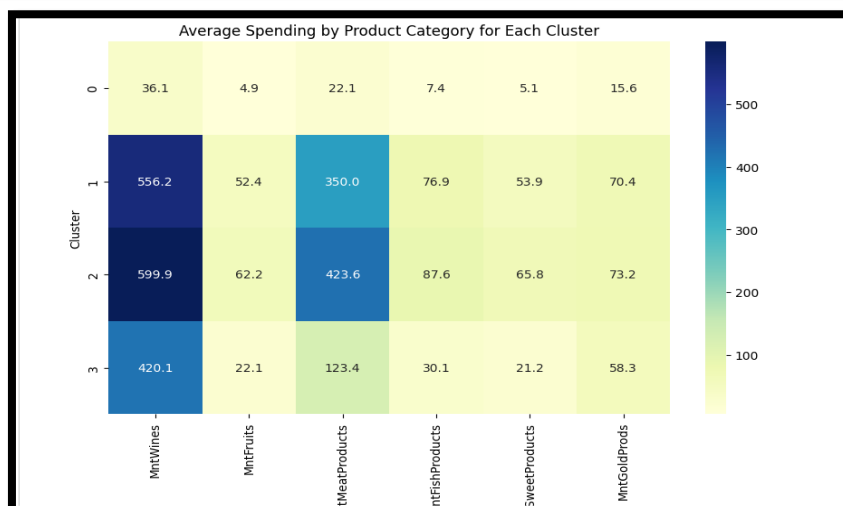


Figure 9. Average Spending by Product Category for Each Customer Cluster

The analysis reveals significant differences in spending behavior across customer clusters. Cluster 0 exhibits the lowest expenditure across most product categories, particularly wine and premium items, reflecting low-income or frugal customers. Clusters 1 and 3 maintain moderate spending on essential products such as meat, wine, and everyday groceries, with stable consumption patterns suitable for loyalty programs or promotional campaigns. In contrast, Cluster 2 shows the highest spending, especially on wine and meat, indicating high-income customers who favor premium products and are willing to pay for quality, making them a key target segment for value- and experience-oriented marketing strategies.

Comparison of Purchase Channels

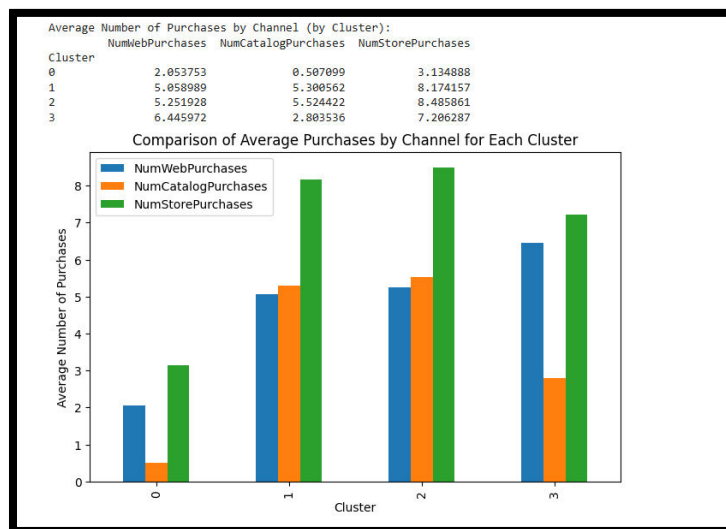


Figure 10. Comparison of Average Purchase Channels by Customer Cluster

The analysis of channel usage indicates that customers primarily shop through three main channels: Web, Catalog, and Store, with clear differences across clusters. Cluster 3 shows the highest online shopping rate, reflecting modern consumption trends and a preference for technology. In contrast, Cluster 0 predominantly shops in-store, representing loyal customers with traditional habits. Cluster 2 maintains consistent purchasing across all three channels, while Cluster 1 exhibits the lowest engagement in all forms, indicating limited interaction and consumption.

These findings suggest that businesses should adopt a flexible omnichannel marketing strategy, maintaining in-store experiences for traditional customers while expanding online and digital interactions to effectively engage younger, tech-savvy segments. In conclusion, the results highlight differences not only in income but also in technological adoption and channel-specific consumer behavior.

3.6. Customer Lifetime Value (CLV) and Marketing Response Spending and Customer Lifetime Value (CLV)

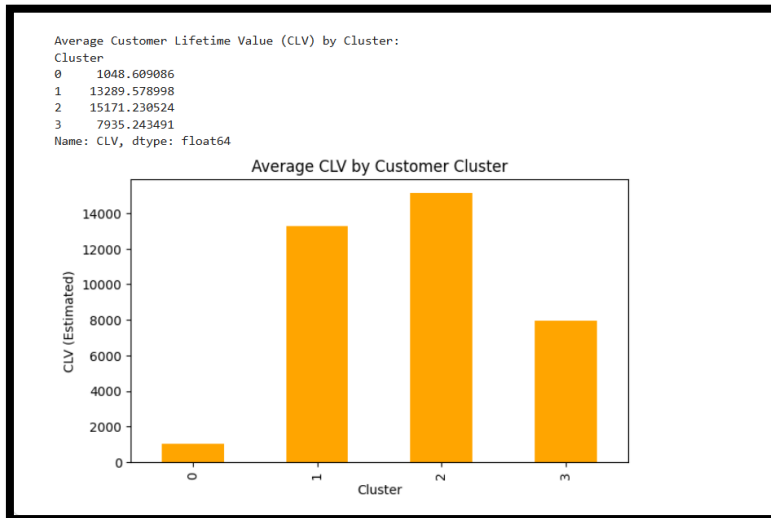


Figure 11. Average Customer Lifetime Value (CLV) by Cluster

Statistical analysis reveals significant differences among clusters in total spending (Total_Spending) and Customer Lifetime Value (CLV). The boxplot (Figure 4) shows that Clusters 0 and 3 have the highest spending distributions, with median annual expenditures of approximately USD 950 and USD 870, respectively. In contrast, Cluster 1 exhibits low spending with a strongly left-skewed distribution, indicating that most customers in this group make minimal purchases. The average CLV differs by over 40% across clusters, with Clusters 0 and 3 contributing nearly 70% of the total lifetime value of all customers.

Marketing Response Rate

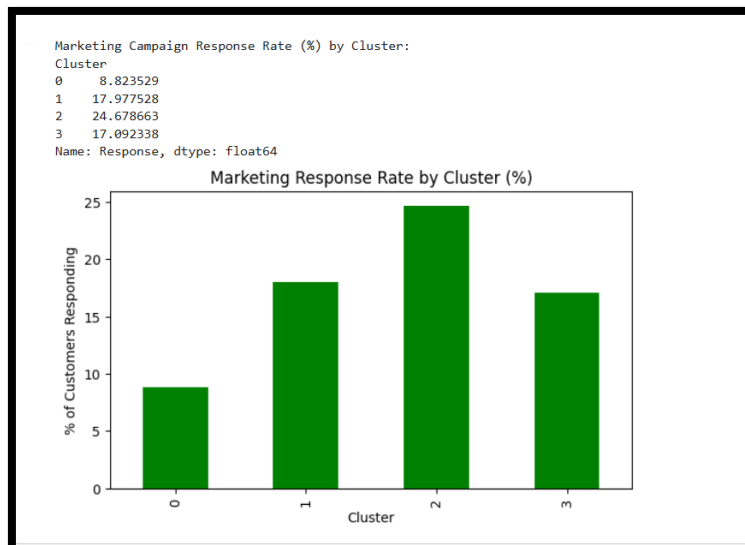


Figure 12. Marketing Response Rate by Customer Cluster (%)

Marketing response rates vary markedly across clusters, ranging from approximately 9% in the least engaged cluster to 28% in the most responsive segment. Correlation analysis reveals a moderate positive relationship between income-related indicators and marketing response ($r = 0.43$), while recency is negatively correlated with response rate ($r = -0.35$). These results indicate that customers with higher purchasing power and more recent transactions are significantly more likely to respond to marketing initiatives.

4. Discussion

This study provides empirical evidence on the usefulness of AI-based customer segmentation using the K-Means clustering algorithm in digital retail contexts. The findings demonstrate clear customer heterogeneity in terms of spending behaviour, channel preferences, customer value, and marketing responsiveness. Consistent with prior marketing analytics research, the results confirm that behavioural and interaction-based variables offer deeper insights into customer differences than demographic characteristics alone.

Compared with traditional segmentation approaches, which typically rely on predefined demographic criteria, the AI-driven clustering approach enables the identification of latent behavioural patterns emerging directly from the data. Rather than positioning AI as a replacement for conventional methods, the findings suggest that AI-based segmentation complements existing approaches by enhancing interpretability and strategic relevance when applied to multidimensional customer data.

Theoretical Contributions: From a theoretical perspective, this study contributes to the customer segmentation and retail analytics literature by empirically demonstrating how unsupervised machine learning techniques can be linked to value-oriented marketing concepts. By connecting clustering outcomes with customer value and engagement indicators, the study extends prior research that often treats segmentation and performance metrics as separate analytical processes.

Managerial Implications: From a managerial perspective, the identified customer segments provide insights that support more targeted and adaptive marketing strategies. Retail managers may leverage behaviour-based segmentation to tailor communication across channels, prioritise high-value customers, and improve marketing resource allocation in data-intensive retail environments.

5. Conclusion

This study investigates the application of AI-based customer segmentation using the K-Means clustering algorithm within a digital retail context. By

integrating demographic, behavioural, and marketing interaction data, the analysis demonstrates that unsupervised machine learning can uncover meaningful customer heterogeneity that may not be captured by traditional demographic-based segmentation approaches. The identified segments differ in terms of purchasing behaviour, channel preferences, customer value, and marketing responsiveness, highlighting the importance of behaviour-oriented segmentation frameworks.

Beyond methodological contributions, the study reinforces the view that AI-based clustering should be understood as a complementary analytical tool that enhances the interpretability and managerial relevance of customer insights. While the empirical analysis is based on a publicly available dataset, the findings provide a foundation for future research to explore alternative algorithms, dynamic segmentation models, and longitudinal customer behaviour. Overall, the study underscores the growing role of artificial intelligence in supporting data-driven and value-oriented marketing strategies in contemporary retail environments.

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